# Neural Networks for Named Entity Recognition

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(slides originally by Dr. Fabienne Braune)

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# Outline

# Named Entity Recognition

# Task

Find segments of entity mentions in input text and tag with labels.

Example inputs:

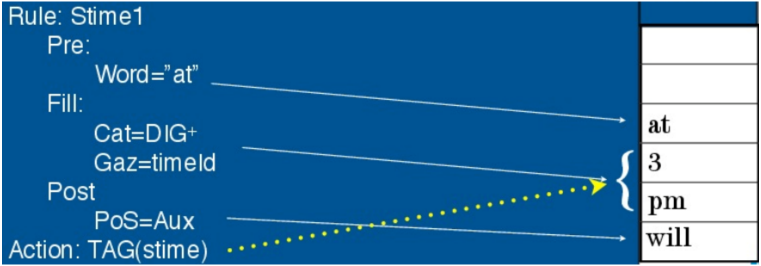
- *Trump attacks BMW and Mercedes*
- *U.N. official Ekeus heads for Baghdad*

Example labels (coarse grained):

- persons PER
- locations LOC
- organizations ORG
- names NAME
- other MISC

# Rule-based approaches

- A collection of rules to detect entities
- High precision vs. low recall
- Interpretable
- Time consuming to build and domain knowledge is needed




(Fabio Ciravegna, University of Sheffield)

# Classification-based approaches

Given input segment, train classifier to tell:

- Is this segment a Named Entity ?
- Give the corresponding Tag

Classification task:

*Trump attacks BMW and Mercedes*

Is Trump a named entity ?

Yes, it is a person (PER)

Desired outputs:

- *Trump PER attacks BMW ORG and Mercedes ORG*
- *U.N. ORG official Ekeus PER heads for Baghdad LOC*

# Labeled data

Example annotations (CoNLL-2003):

| Surface | Tag |
|---|---|
| U.N. | I-ORG |
| official | O |
| Ekeus | I-PER |
| heads | O |
| for | O |
| Baghdad | I-LOC |
| . | O |

| Scheme | Begin | Inside | End | Single | Other |
|---|---|---|---|---|---|
| IOB | B-X | I-X | I-X | B-X | O |
| IOE | I-X | I-X | E-X | E-X | O |
| IOBES | B-X | I-X | E-X | S-X | O |

(Collobert et al., 2011)

# Classification-based approaches

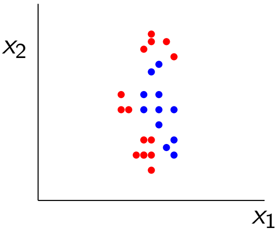
- Classifier combination with engineered features (Florian et al., 2003)
  - Manually engineer features
    - words
    - POS tags
    - prefixes and suffixes
    - large (external) gazetteer
  - 88.76 F1
- Semi-supervised learning with linear models (Ando and Zhang, 2005)
  - Train linear model on annotated data
  - Add non-annotated data
  - 89.31 F1

# Classification-based approaches

- Differences to rule-based:
  - Feature sets vs. rules
  - Less domain knowledge is needed
  - Faster to adapt systems
  - Annotated data is needed
- Next: neural networks
  - even less manual work

# Feedforward Neural Networks: Recap

# Motivation




Linear models not suited to learn non-linear decision boundaries.

Neural networks can do that

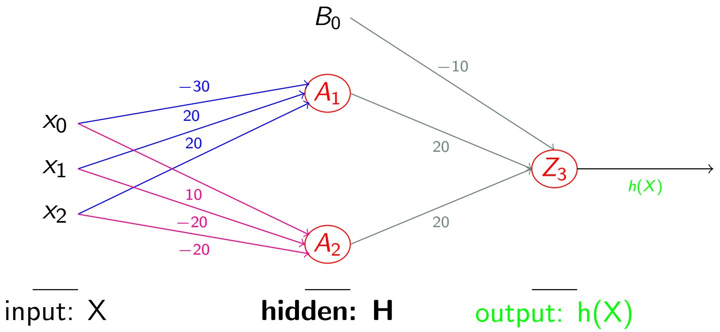
$\rightarrow$ Through composition of non-linear functions

$\rightarrow$ Learn relevant features from (almost) raw text

  $\rightarrow$ No need for manual feature engineering

  $\rightarrow$ learned by network

# Feedforward Neural Network




Computation of hidden layer **H**:

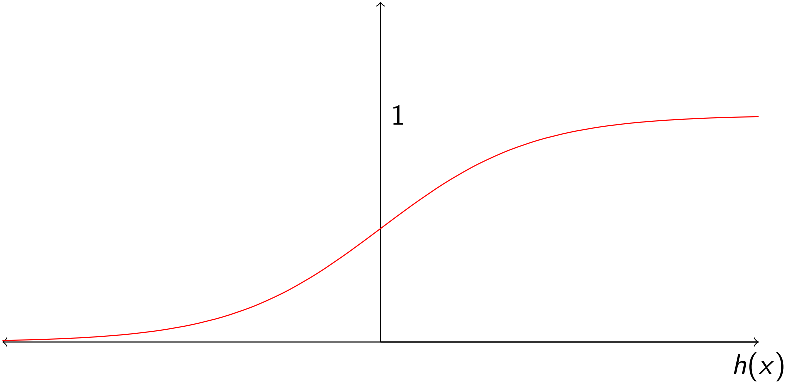
- $A_1 = \sigma(X \cdot \Theta_1)$
- $A_2 = \sigma(X \cdot \Theta_2)$
- $B_0 = 1$ (bias term)

Computation of output unit h(X):

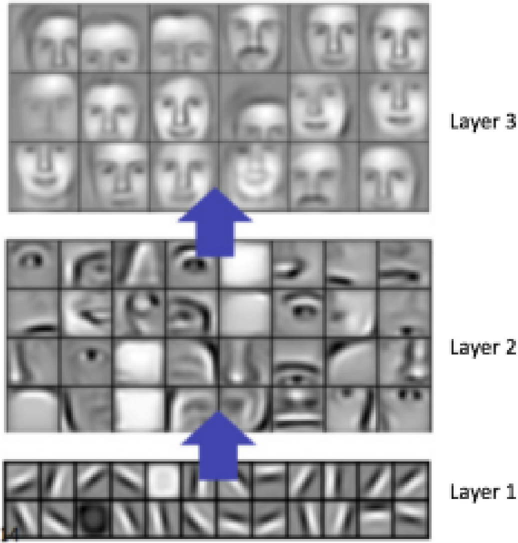
- $h(X) = \sigma(\mathbf{H} \cdot \Theta_3)$

# Non-linear activation function

The **sigmoid function** $\sigma(Z)$ is often used



# Learning features from raw input




(Lee et al., 2009)

# Feedforward neural network

*Trump attacks BMW and Mercedes*

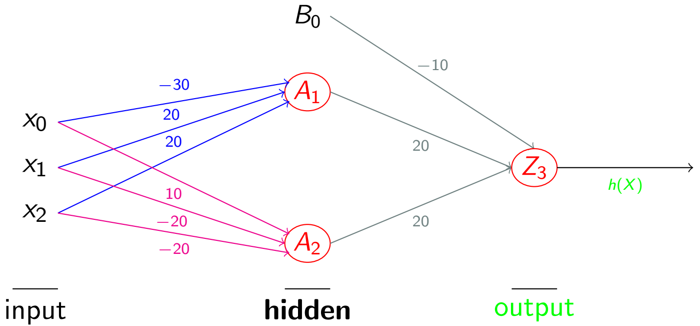
Binray NER task: Is the segment from position 1 to 2 a Named Entity?

**Neural network**: $h(X) = \sigma(\mathbf{H} \cdot \Theta_n)$, with:

$$\mathbf{H} = \begin{bmatrix} B_0 = 1 \\ A_1 = \sigma(X \cdot \Theta_1) \\ A_2 = \sigma(X \cdot \Theta_2) \\ \dots \\ A_j = \sigma(X \cdot \Theta_j) \end{bmatrix}$$

Prediction: If $h(X) > 0.5$, yes. Otherwise, no.

# Feedforward Neural Network




If weights are all random output will be random

→ Predictions will be bad

→ Get the right weights

# Getting the right weights

Training: Find weight matrices $U = (\Theta_1, \Theta_2)$ and $V = \Theta_3$ such that $h(X)$ is the **correct answer** as many times as possible.

$\rightarrow$ Given a set $T$ of training examples $t_1, \cdots t_n$ with **correct labels** $\mathbf{y_i}$, find $U = (\Theta_1, \Theta_2)$ and $V = \Theta_3$ such that $h(X) = \mathbf{y_i}$ for as many $t_i$ as possible.

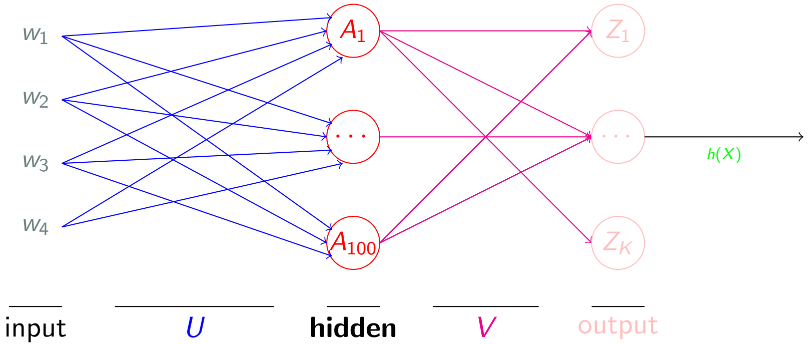
$\rightarrow$ Computation of $h(X)$ called forward propagation

$\rightarrow$ $U = (\Theta_1, \Theta_2)$ and $V = \Theta_3$ with error back propagation

# Multi-class classification

- More than two labels
- Instead of "yes" and "no", predict $c_i \in C = \{c_1, \cdots, c_k\}$
- NER: Is this segment a location, name, person ...
- **Use k output units**, where $k$ is number of classes
  - Output layer instead of unit
  - Use softmax to obtain value between 0 and 1 for each class
  - Highest value is right class

# Multi-class classification



# Neural Networks for NER

# Feedforward Neural Network for NER

Training example: *Trump attacks BMW (ORG) and Mercedes*

Neural network input:

Look at word window around BMW

$\rightarrow$ $\mathbf{Trump}_{-2}$ $\mathbf{attacks}_{-1}$ **BMW** $\mathbf{and}_{1}$ $\mathbf{Mercedes}_{2}$

$\rightarrow$ each word $w_i$ is represented as one-hot vector

$\rightarrow$ $w_i = \left[0, 1, 0, 0, ..., 0\right]$

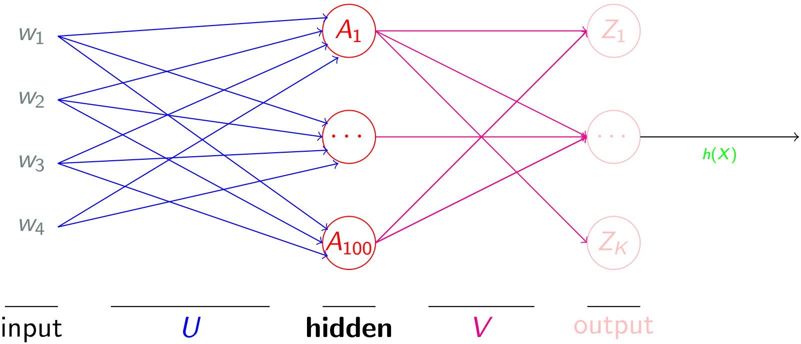
Neural network training:

Predict corresponding label (forward propagation)

$\rightarrow$ should be organization (ORG)

Train weights by backpropagating error

# Feedforward Neural Network for NER




- Input: one-hot word representations $w_i$
- Hidden layer: learns to detect higher level features
  - e.g.: *at ... pm*
- Output: predicted label

# Weight training

Training: Find weight matrices $U$ and $V$ such that $h(X)$ is the **correct answer** as many times as possible.

→ Given a set $T$ of training examples $t_1, \cdots t_n$ with **correct labels** $\mathbf{y_i}$, find $U$ and $V$ such that $h(X) = \mathbf{y_i}$ for as many $t_i$ as possible.

→ Computation of $h(X)$ with forward propagation

→ $U$ and $V$ with error back propagation

# Backpropagation

Goal of training: adjust weights such that correct label is predicted

$\rightarrow$ Error between correct label and prediction is minimal

Compute error at output:

Compare

- output: $h(x^i) = [0.01,\ 0.1,\ 0.001,\ 0.95,\ ...,\ 0.01]$
- correct label: $y^i = [0,\ 0,\ 1,\ 0,\ ...,\ 0]$

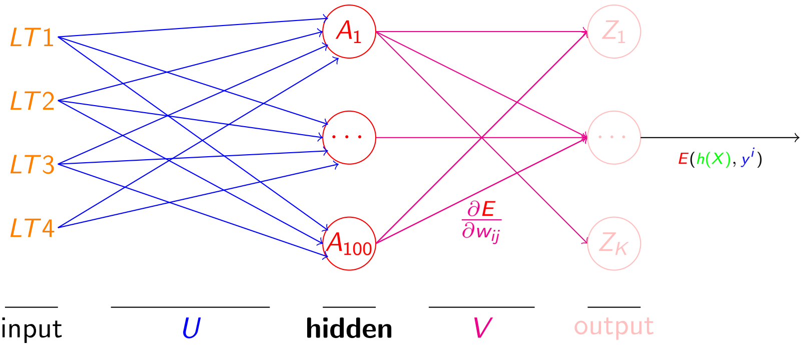
$$E = \frac{1}{2} \sum_{j=1}^{n} (y^i_j - h(x^i)_j)^2 \text{ (mean squared)}$$

Search influence of weight on error:

$$\frac{\partial E}{\partial w_{ij}}$$

$w_{ij}$: single weight in weight matrix

# Backpropagation




Backpropagation:

→ E needs to go through output neuron.

→ Chain rule: $\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial O_j} \frac{\partial O_j}{\partial Z_j} \frac{\partial Z_j}{\partial w_{ij}}$

# Weight training

Gradient descent: for each batch of training examples

1. Forward propagation to get predictions
2. Backpropagation of error
   - Gives gradient of E given input
3. Modify weights
4. Goto 1 until convergence

# Outcome

- Hidden layer is able to learn higher level features of words
  - *Cars are* **produced at BMW**
- Not enough to get good performance
- A simple index does not carry much information about a given word
  - $w_{BMW} \quad = [1, 0, 0, 0, ..., 0]$
  - $w_{Mercedes} = [0, 1, 0, 0, ..., 0]$
  - $w_{happiness} = [0, 0, 1, 0, ..., 0]$

- This would be better
  - $w_{BMW} \quad = [1, 0, 0, 0, ..., 0]$
  - $w_{Mercedes} = [1, 0, 0, 0, ..., 0]$
  - $w_{happiness} = [0, 0, 1, 0, ..., 0]$

# Lookup (Embedding) Layer

- Learn features for words as well
- Similar words have similar features
- Lookup table layer:
  - embeds each one-hot encoded word $w_i$
  - to a feature vector $LT_i$

  - $w_{BMW} = [0.5, 0.5, 0.0, 0.0, ..., 0.0]$
  - $w_{Mercedes} = [0.5, 0.0, 0.5, 0.0, ..., 0.0]$

# Dot product with (trained) weight vector

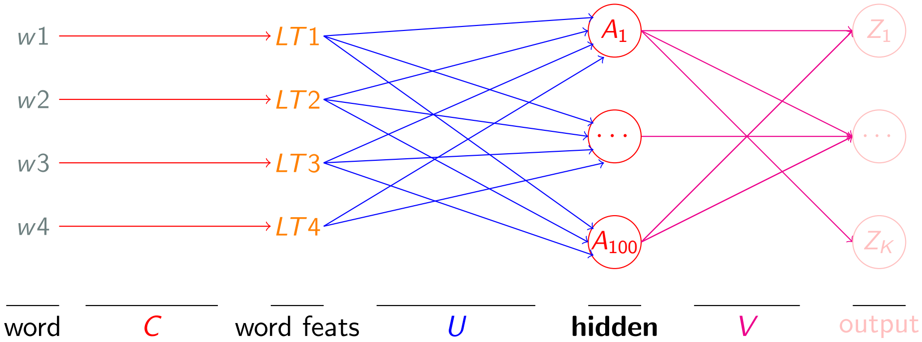
$W = \{\text{the,cat,on,table,chair}\}$

$$w_{table} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} \quad C = \begin{bmatrix} 0.02 & 0.1 & 0.05 & 0.03 & 0.01 \\ 0.15 & 0.2 & 0.01 & 0.02 & 0.11 \\ 0.03 & 0.1 & 0.04 & 0.04 & 0.12 \end{bmatrix}$$

$$LT_{table} = w_{table} \cdot C^T = \begin{bmatrix} 0.03 \\ 0.02 \\ 0.04 \end{bmatrix}$$

Words get mapped to lower dimension
$\rightarrow$ Hyperparameter to be set

# Feedforward Neural Network with Lookup Table




C is shared!

# Dot product with (initial) weight vector

$W = \{\text{the,cat,on,table,chair}\}$

$$w_{table} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} \quad C = \begin{bmatrix} 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \end{bmatrix}$$

$$LT_{table} = w_{table} \cdot C^T = \begin{bmatrix} 0.01 \\ 0.01 \\ 0.01 \end{bmatrix}$$

Feature vectors same for all words.

# Weight training

Training: Find weight matrices $C$, $U$ and $V$ such that $h(X)$ is the **correct answer** as many times as possible.

$\rightarrow$ Given a set $T$ of training examples $t_1, \cdots t_n$ with **correct labels $\mathbf{y_i}$**, find $C$, $U$ and $V$ such that $h(X) = \mathbf{y_i}$ for as many $t_i$ as possible.

$\rightarrow$ Computation of $h(X)$ with forward propagation

$\rightarrow$ $C$, $U$ and $V$ with error back propagation

$\rightarrow$ Lookup matrix $C$ trained with NER training data

$\rightarrow$ Word feature vectors are trained towards NER

# Results

Classifier combination with engineered features (Florian et al. 2003)

- 88.76 F1

Semi-supervised learning with linear models (Ando and Zhang 2005)

- 89.31 F1

Feedforward Neural Networks for NER (Collobert et al., 2011):

- With raw words 81.74

# NER trained word embeddings

Word embeddings trained on NER task

- (Collobert et al. 2011)

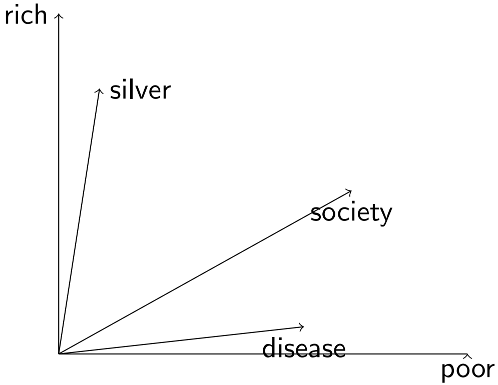
→ Small amount of **annotated** data.

- Closest words to France
  - Persuade
  - Faw
  - Blackstock
- Closest words to XBOX
  - Decadent
  - Divo
  - Versus

# Adding Pre-trained Word Embeddings

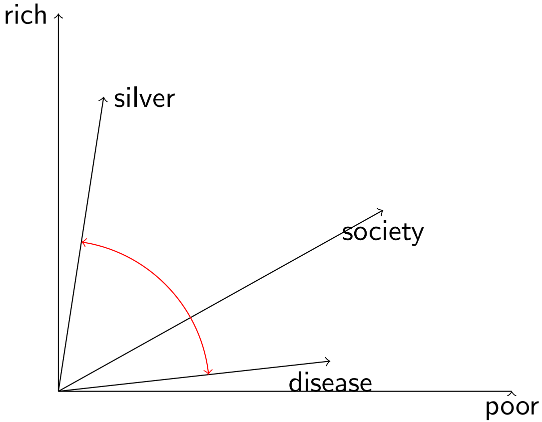
# Word Embeddings

- Representation of words in vector space



# Word Embeddings

- Similar words are close to each other
  $\rightarrow$ Similarity is the cosine of the angle between two word vectors



# Learning word embeddings

Count-based methods:

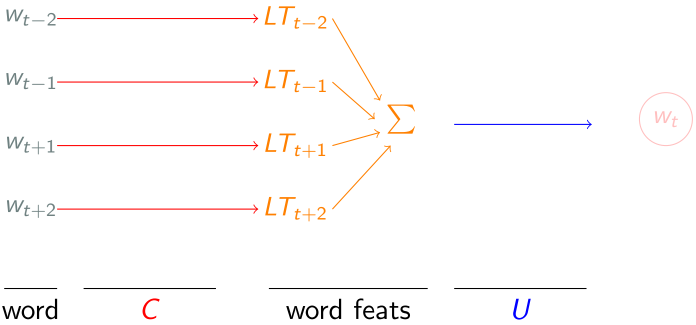
- Compute cooccurrence statistics
- Learn high-dimensional representation
- Map sparse high-dimensional vectors to small dense representation
- Matrix factorization approaches: SVD

Neural networks:

- Predict a word from its neighbors
- Learn (small) embedding vectors
- Word2Vec: CBOW and skipgram Mikolov et al. (2013)
- Language Modeling Task
- ELMo, BERT Peters et al. (2018); Devlin et al. (2018)

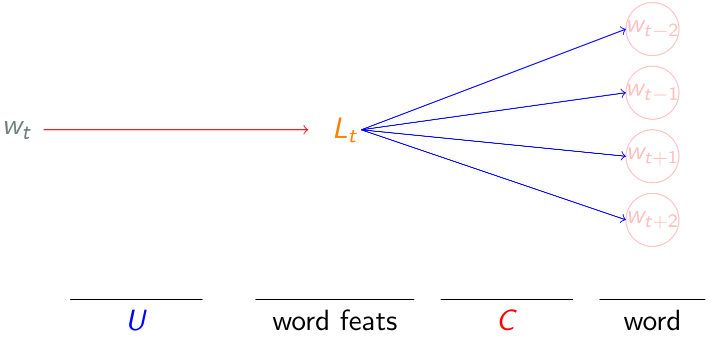
# Learning word embeddings with CBOW

Training example: *Trump attacks* *BMW* *and Mercedes*



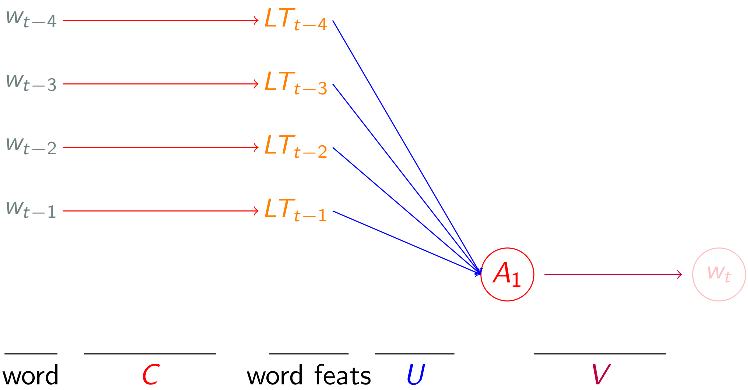
# Learning word embeddings with skip-gram

Training example: *Trump attacks BMW and Mercedes*



# Learning word embeddings with Language Modeling

Training example: *Trump attacks BMW and Mercedes*



# Word Embeddings for NER

- Train word embeddings in advance:
  - $\rightarrow$ Use large amounts of non-annotated data
  - $\rightarrow$ No need for NER training data
  - $\rightarrow$ Labels are words $w_t$
- Replace lookup table $C$ (randomly initialized) with $C$ (pre-trained)

# NER trained word embeddings

Word embeddings trained on NER task

- (Collobert et al. 2011)

→ Small amount of **annotated** data.

- Closest words to France
  - Persuade
  - Faw
  - Blackstock
- Closest words to XBOX
  - Decadent
  - Divo
  - Versus

# NER trained word embeddings

Pre-trained word embeddings trained
$\rightarrow$ Large amount of **non-annotated** data.

- Closest words to France
  - Austria
  - Belgium
  - Germany
- Closest words to XBOX
  - Amiga
  - Playstation
  - MSX

# Results

Classifier combination with engineered features (Florian et al. 2003)

- 88.76 F1

Semi-supervised learning with linear models (Ando and Zhang 2005)

- 89.31 F1

Feedforward Neural Networks for NER (Collobert et al. 2011):

- With raw words 81.74
- With pre-trained word embeddings 88.67
- Using a gazetteer 89.59

# Results

- Pre-trained word embeddings yield significant improvements
- Hidden layer is able to learn higher level features of words
  - *Cars are* **produced at BMW**
- Word features:
  - $w_{BMW} = [0.5, 0.5, 0.0, 0.0, ..., 0.0]$
  - $w_{Mercedes} = [0.5, 0.0, 0.5, 0.0, ..., 0.0]$
  - $w_{happiness} = [0.0, 0.0, 0.0, 1.0, ..., 0.0]$
- It also helps the problem of out-of-vocabulary words

- The power is in exploiting large unlabeled data
- insted of relying only on small labeled data

# Sequence Tagging with RNNs and CRFs

# NER as sequence tagging

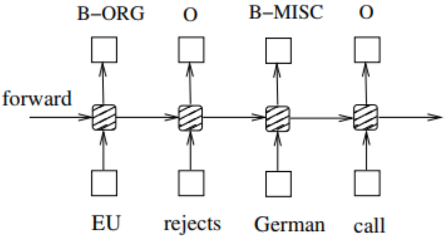
- Sequential input
  - Classification approaches (linear or NN) looked at a window around the input word
  - Limitation of window size
    - too small → loosing information
    - too large → noise or data scarcity

  **Let's have a party at JFK**

  - Read words sequentially and keep relevant information only
- Sequence of tags
  - IOB format: beginning and inside tags
  - Some tags shouldn't follow each other
  - Output labels sequentially word-by-word

  **The seminar starts tomorrow 4pm**

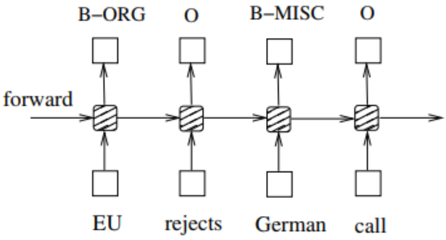
# Recurrent Neural Network (RNN)




(Huang et al., 2015)

- Reads the input sequentially
- At time step t:
  - $h_t = f(h_{t-1}, x_t; \theta_1)$
    - e.g. $h_t = \sigma(h_{t-1} * U + x_t * V)$
  - $o_t = g(h_t; \theta_2)$
    - e.g. $o_t = \sigma(h_t * W)$
- Parameters are shared for each time step
- Multiple variations: LSTM, GRU, etc.

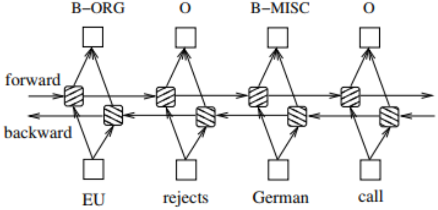
# RNNs for NER




(Huang et al., 2015)

- Input: words
- Lookup layer
  - learn embeddings from scratch
  - or used pre-trained embeddings
- Probabilities of each NER tag
- Example: **I'm traveling to the EU**

# Bidirectional RNNs

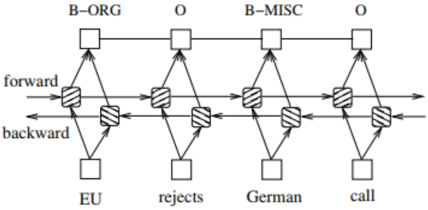



(Huang et al., 2015)

**The EU is very far from the US**

- Read the input both from left-to-right and right-to-left
- Concatenate the hidden states to get the output
  - $o_t = g(\overrightarrow{h_t} | \overleftarrow{h_t}; \theta_2)$

# Conditional Random Fields (CRF)




(Huang et al., 2015)

- Tag at time step $t$ should be dependent on the RNN output at $t$ and the tag at $t-1$ as well
- CRF adds (soft) constrains on the final predicted tags ensuring they are valid given previous tags
  - Transition matrix $T_{i,j}$: probability of tag $j$ given that previous tag was $i$

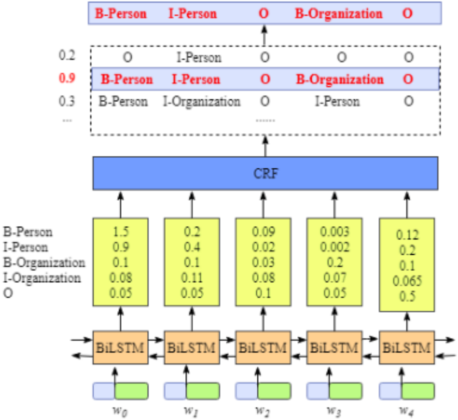
# CRF transition matrix

| From \ To | O | B-LOC | I-LOC | B-MISC | I-MISC | B-ORG | I-ORG | B-PER |
|---|---|---|---|---|---|---|---|---|
| O | 3.281 | 2.204 | 0.0 | 2.101 | 0.0 | 3.468 | 0.0 | 2.325 |
| B-LOC | -0.259 | -0.098 | 4.058 | 0.0 | 0.0 | 0.0 | 0.0 | -0.212 |
| I-LOC | -0.173 | -0.609 | 3.436 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| B-MISC | -0.673 | -0.341 | 0.0 | 0.0 | 4.069 | -0.308 | 0.0 | -0.331 |
| I-MISC | -0.803 | -0.998 | 0.0 | -0.519 | 4.977 | -0.817 | 0.0 | -0.611 |
| B-ORG | -0.096 | -0.242 | 0.0 | -0.57 | 0.0 | -1.012 | 4.739 | -0.306 |
| I-ORG | -0.339 | -1.758 | 0.0 | -0.841 | 0.0 | -1.382 | 5.062 | -0.472 |
| B-PER | -0.4 | -0.851 | 0.0 | 0.0 | 0.0 | -1.013 | 0.0 | -0.937 |
| I-PER | -0.676 | -0.47 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | -0.659 |

**CRF State Transition Matrix**

(Image taken from https://eli5.readthedocs.io sklearn tutorial)

# RNN + CRF for NER




**CRF Input Matrix**

(Image taken from https://createmomo.github.io/)

- Prediction: tag sequence probability is calculated using RNN and transition probabilities (Viterbi algorithm)

# Results

Classifier combination with engineered features (Florian et al. 2003)

- 88.76 F1

Semi-supervised learning with linear models (Ando and Zhang 2005)

- 89.31 F1

Feedforward Neural Networks for NER (Collobert et al. 2011):

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BI-LSTM-CRF

- 90.10

# Bilingual Word Embeddings

# Bilingual transfer learning

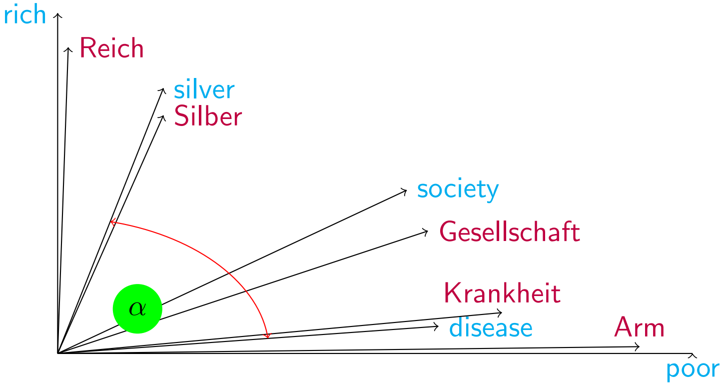
- For many low-resource languages we do not have enough training data for NER
- Use knowledge from resource rich langauages
- Translate data to the target language
  - Parallel data is needed for the translation system
- Target language words are OOVs for a system trained on the source language
  - similarity of source and target words $\rightarrow$ bilingual word embeddings

# Bilingual Word Spaces

Representation of words in two languages in same semantic space:

$\rightarrow$ Similar words are close to each other

$\rightarrow$ Given by cosine



# Learning Bilingual Word Embeddings

- Learn bilingual embeddings from parallel data

  Hermann and Blunsom (2014), Gouws et al. (2015), Gouws and Søgaard (2015), Duong et al. (2016)

  Need for parallel data

- Learn bilingual embeddings or lexicon from document-aligned data

  Vulic and Moens (2015); Vulic and Korhonen (2016)

  Need document-aligned data

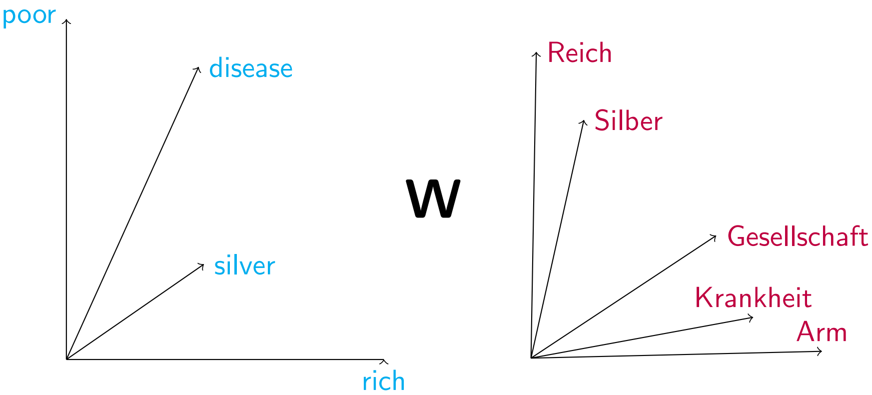
- Learn monolingual word embeddings and map using seed lexicon

  Mikolov et al. (2013); Faruqui and Dyer (2014); Lazaridou et al. (2015)

  Need seed lexicon

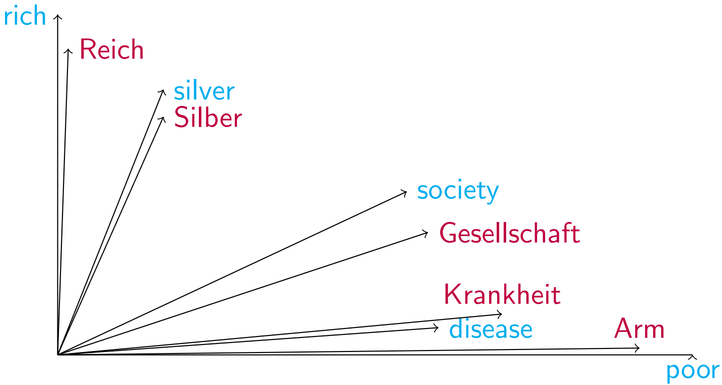
# Post-hoc mapping (with seed lexicon)

- Learn monolingual word embeddings
- Learn a linear mapping $W$



# Post-hoc mapping

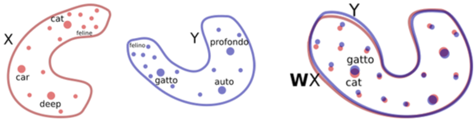
- Project source words into target space



# Post-hoc Mapping with seed lexicon

1. Train monolingual word embeddings (Word2vec) in English
   - Need English monolingual data
2. Train monolingual word embeddings (Word2vec) in German
   - Need German monolingual data
3. Learn mapping **W** using a seed lexicon
   - Need a list of 5000 English words and their translation

# Learning $W$ with Regression




(Conneau et al., 2017)

Regression (Mikolov et al. (2013))

$$\mathbf{W}^* = \arg\min_{\mathbf{W}} \sum_{\mathbf{i}}^{\mathbf{n}} || \, \mathbf{x_i W} - \mathbf{y_i} \, ||^{\mathbf{2}}$$

$x_i$ : **embedding** of i-th source (English) word in the seed lexicon.

$y_i$ : **embedding** of i-th target (German) word in the seed lexicon.

# Learning $W$ with Ridge Regression

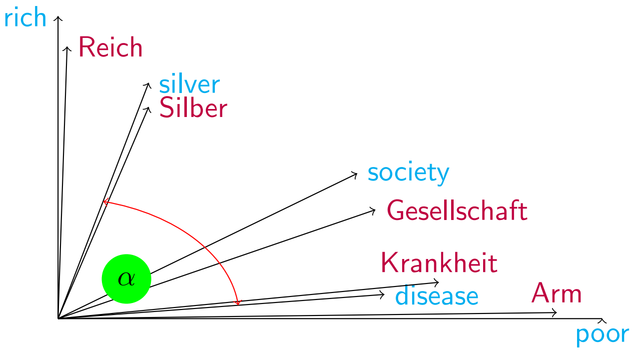
Regression (Mikolov et al. (2013))

$$\mathbf{W}^* = \arg\min_{\mathbf{W}} \sum_{\mathbf{i}}^{\mathbf{n}} || \, \mathbf{x_i W} - \mathbf{y_i} \, ||^{\mathbf{2}}$$

- Predict projection $\mathbf{y*}$ by computing $\mathbf{x_i W}$
- Compute squared error between $\mathbf{y*}$ and $\mathbf{y_i}$
  - Correct translation $t_i$ given in seed lexicon
  - Vector representation $\mathbf{y_i}$ is given by embedding of $t_i$
- Find $\mathbf{W}$ such that squared error over training set is minimal

# Bilingual lexicon induction

- Task to evaluate bilingual word embeddings intrinsically
- Given a set of source words, find the corresponding translations:
  - Given silver, find its vector in the BWE
  - Retrieve the German word whose vector is closest (cosine distance)



# Bilingual lexicon induction with ridge regression

Data: WMT 2011 training data for English, Spanish, Czech
Seed: 5000 most frequent words translated with Google Translate
Test: 1000 next frequent words translated with Google Translate

$\rightarrow$ Removed digits, punctuation and transliterations

| Languages | top-1 | top-5 |
|---|---|---|
| En-Es | 33 % | 51 % |
| Es-En | 35 % | 50 % |
| En-Cz | 27 % | 47 % |
| Cz-En | 23 % | 42 % |
| + Es-En | 53 % | 80 % |

$\rightarrow$ with spanish google news

# NER Results

- Use the bilingual word embeddings to initialize the lookup table in the NER classifier
- Ni et al. (2017)
- Spanish:
  - supervised: 80.6
  - transfer learning: 57.4
- Dutch:
  - supervised: 82.3
  - transfer learning: 60.3
- German:
  - supervised: 71.8
  - transfer learning: 54.4

# Summary

- Using neural networks for NER yields good results using (almost) raw representations of words
- Word embeddings can be learned automatically on large amounts of non-annotated data
- Giving pre-trained word embeddings as input to neural networks improve end-to-end task
- Bilingual word embeddings make it possible to transfer knowledge from resource rich languages

Thank you !

# References I


Ando, R. K. and Zhang, T. (2005). A framework for learning predictive structures from multiple tasks and unlabeled data. *Journal of Machine Learning Research*.

Collobert, R., Weston, J., Bottou, L., Karlen, M., Kavukcuoglu, K., and Kuksa, P. (2011). Natural language processing (almost) from scratch. *Journal of Machine Learning Research*.

Conneau, A., Lample, G., Ranzato, M., Denoyer, L., and Jégou, H. (2017). Word translation without parallel data. *arXiv preprint arXiv:1710.04087*.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

Duong, L., Kanayama, H., Ma, T., Bird, S., and Cohn, T. (2016). Learning crosslingual word embeddings without bilingual corpora. In *Proc. EMNLP*.

# References II


Faruqui, M. and Dyer, C. (2014). Improving vector space word representations using multilingual correlation. In *Proc. EACL*.

Florian, R., Ittycheriah, A., Jing, H., and Zhang, T. (2003). Named entity recognition through classifier combination. In *Proceedings of the seventh conference on Natural language learning at HLT-NAACL 2003-Volume 4*.

Gouws, S., Bengio, Y., and Corrado, G. (2015). Bilbowa: Fast bilingual distributed representations without word alignments. In *Proc. ICML*.

Gouws, S. and Søgaard, A. (2015). Simple task-specific bilingual word embeddings. In *Proc. NAACL*.

Hermann, K. M. and Blunsom, P. (2014). Multilingual models for compositional distributed semantics. In *Proc. ACL*, pages 58–68, Baltimore, Maryland. Association for Computational Linguistics.

Huang, Z., Xu, W., and Yu, K. (2015). Bidirectional LSTM-CRF models for sequence tagging. *arXiv preprint arXiv:1508.01991*.

# References III


Lazaridou, A., Dinu, G., and Baroni, M. (2015). Hubness and pollution: Delving into cross-space mapping for zero-shot learning. In *Proc. ACL*.

Lee, H., Grosse, R., Ranganath, R., and Ng, A. Y. (2009). Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations. In *Proceedings of the 26th annual international conference on machine learning*.

Mikolov, T., Le, Q. V., and Sutskever, I. (2013). Exploiting similarities among languages for machine translation. *CoRR*, abs/1309.4168.

Ni, J., Dinu, G., and Florian, R. (2017). Weakly supervised cross-lingual named entity recognition via effective annotation and representation projection. *arXiv preprint arXiv:1707.02483*.

Peters, M. E., Neumann, M., Iyyer, M., Gardner, M., Clark, C., Lee, K., and Zettlemoyer, L. (2018). Deep contextualized word representations. In *Proc. of NAACL*.

# References IV

Vulic, I. and Korhonen, A. (2016). On the Role of Seed Lexicons in Learning Bilingual Word Embeddings. In *Proc. ACL*, pages 247–257.

Vulic, I. and Moens, M. (2015). Bilingual word embeddings from non-parallel document-aligned data applied to bilingual lexicon induction. In *Proc. ACL*.